

Moment-generating functions¹

STA 302: Fall 2015

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The change of variables formula

Let X be a random variable.

Let $Y = g(X)$. There are two ways to get $E(Y)$.

- 1 Derive the distribution of Y and compute

$$E(Y) = \int_{-\infty}^{\infty} y f_Y(y) dy$$

- 2 Use the distribution of X , and calculate

$$E(g(X)) = \int_{-\infty}^{\infty} g(x) f_X(x) dx$$

Big theorem: These two expressions are equal.

The change of variables formula is very general

Including but not limited to

$$E(g(X)) = \int_{-\infty}^{\infty} g(x) f_X(x) dx$$

$$E(g(\mathbf{X})) = \int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} g(x_1, \dots, x_p) f_{\mathbf{X}}(x_1, \dots, x_p) dx_1 \dots dx_p$$

$$E(g(X)) = \sum_x g(x) p_X(x)$$

Moment-generating functions

$$M_Y(t) = E(e^{Yt}) = \begin{cases} \int_{-\infty}^{\infty} e^{yt} f_Y(y) dy \\ \sum_y e^{yt} p_Y(y) \end{cases}$$

Properties of moment-generating functions

- Moment-generating functions can be used to generate moments. To get $E(Y^k)$, differentiate $M_Y(t)$ with respect to t . Differentiate k times and set $t = 0$.
- Moment-generating functions correspond uniquely to probability distributions.

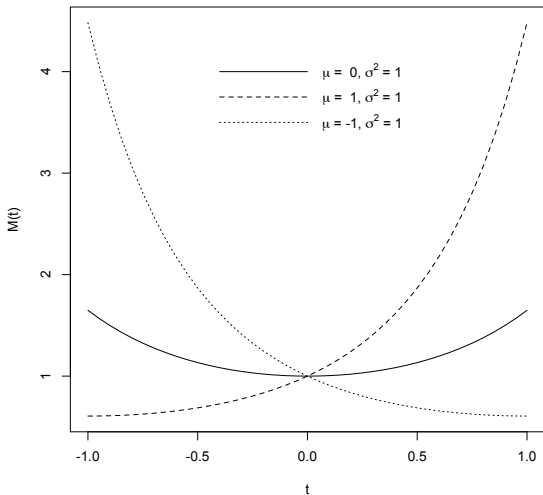
The function $M(t)$ is like a fingerprint of the probability distribution.

$$Y \sim N(\mu, \sigma^2) \text{ if and only if } M_Y(t) = e^{\mu t + \frac{1}{2}\sigma^2 t^2}.$$

$$Y \sim \chi^2(\nu) \text{ if and only if } M_Y(t) = (1 - 2t)^{-\nu/2} \text{ for } t < \frac{1}{2}.$$

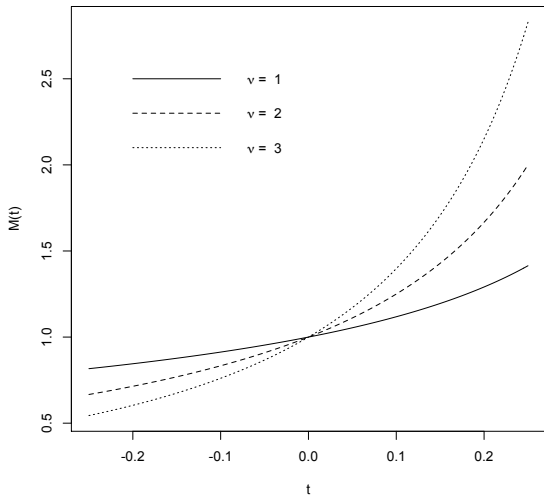
Normal: $M(t) = e^{\mu t + \frac{1}{2}\sigma^2 t^2}$

Fingerprints of the normal distribution



Chi-squared: $M(t) = (1 - 2t)^{-\nu/2}$

Fingerprints of the chi-squared distribution



Example: Using moment-generating functions to prove distribution facts

Let $X \sim N(\mu, \sigma^2)$. Show $Y = \frac{X-\mu}{\sigma} \sim N(0, 1)$

Facts about moment-generating functions

Use these to find distributions of *functions* of random variables

- $M_{aY}(t) = M_Y(at)$
- $M_{Y+a}(t) = e^{at}M_Y(t)$
- If Y_1, \dots, Y_n are independent, $M_{\sum_{i=1}^n Y_i}(t) = \prod_{i=1}^n M_{Y_i}(t)$

A standard example

Using $M_{\sum_{i=1}^n X_i}(t) = \prod_{i=1}^n M_{X_i}(t)$

Let $X_1, \dots, X_n \stackrel{i.i.d.}{\sim} N(\mu, \sigma^2)$, with $Y = \sum_{i=1}^n X_i$. Find the probability distribution of Y .

How about \bar{X} ? Recall $M_{aY}(t) = M_Y(at)$.

Another standard example

Let $X_1, \dots, X_n \stackrel{ind.}{\sim} \chi^2(\nu_i)$, and $Y = \sum_{i=1}^n X_i$. Find the probability distribution of Y .

Less well known

But very useful later

If $W = W_1 + W_2$ with W_1 and W_2 independent,
 $W \sim \chi^2(\nu_1 + \nu_2)$ and $W_2 \sim \chi^2(\nu_2)$ then $W_1 \sim \chi^2(\nu_1)$.

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<http://www.utstat.toronto.edu/~brunner/oldclass/302f15>